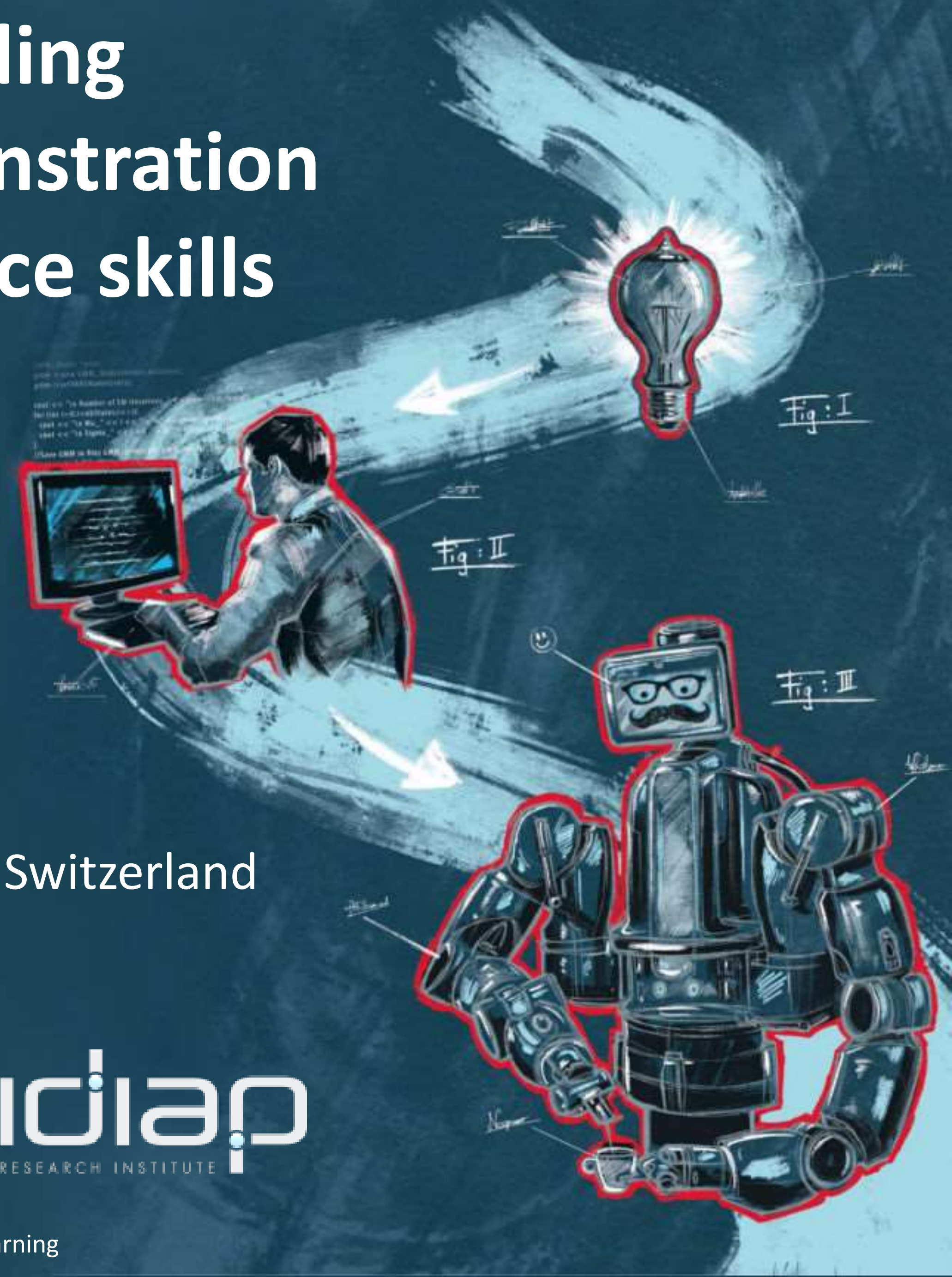
Challenges in extending learning from demonstration to variable impedance skills



Sylvain Calinon

Senior Researcher

Idiap Research Institute, Martigny, Switzerland

Lecturer

EPFL, Lausanne, Switzerland

External Collaborator

IIT, Genoa, Italy

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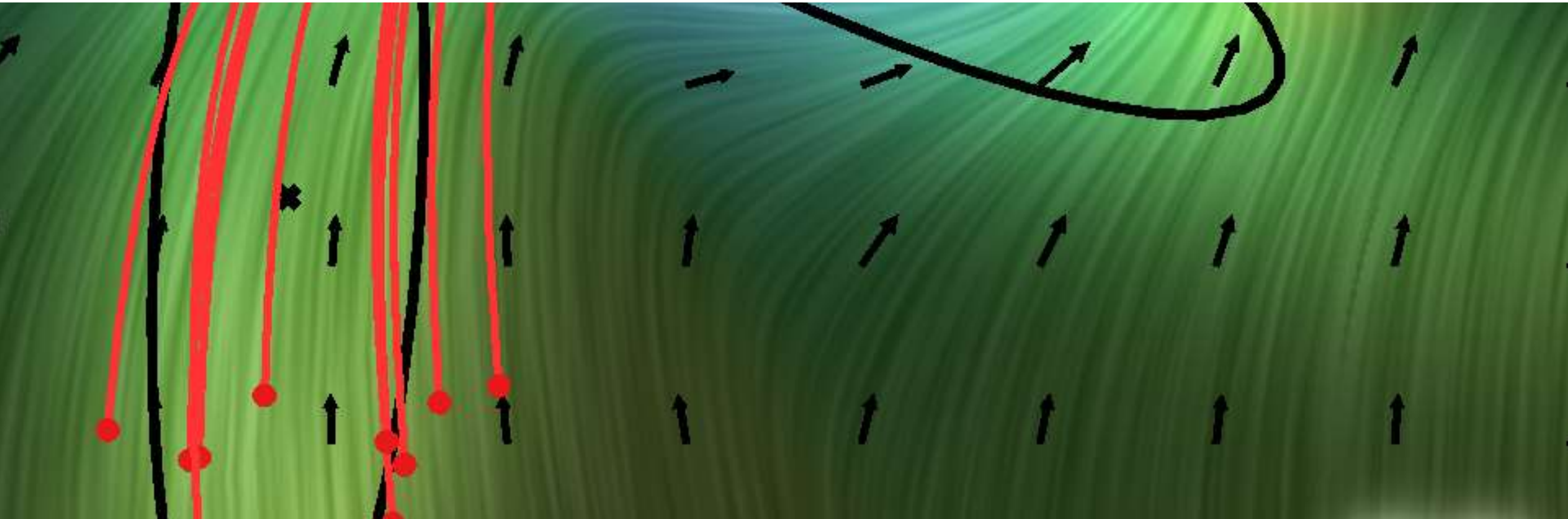
Artificial Intelligence for Society

Research Groups:

- Speech & Audio Processing
- Natural Language Understanding
- Perception & Activity Understanding
- Machine Learning
- Social Computing
- Biometrics Security and Privacy
- Biosignal Processing
- Computational Bioimaging
- Energy Informatics
- Uncertainty Quantification and Optimal Design
- **Robot Learning & Interaction**

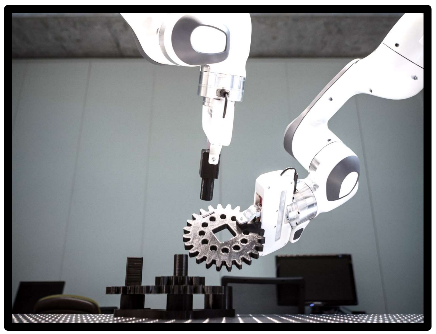
Research
Education
Technology transfer

Finding *Priors* that are expressive enough to be used in a wide range of tasks

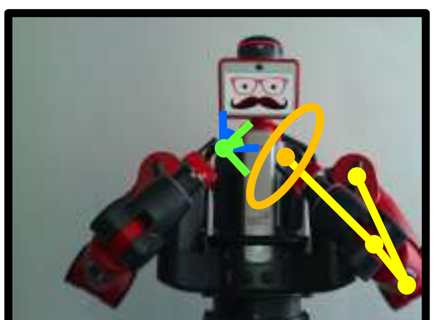


Outline

Prior 1: Natural movements are driven by minimal intervention control principles



Prior 2: Actions often relate to objects, tools or body landmarks



Prior 3: Diverse data in robotics lie on structured manifolds

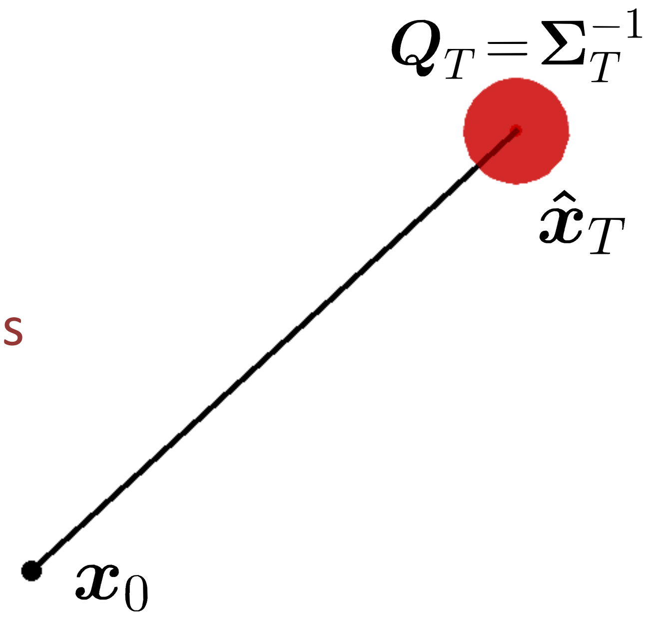
Learning minimal intervention controllers

Track path! Use low control commands!

$$\min_{\boldsymbol{u}} \sum_{t=1}^{T} \boxed{\left\|\hat{\boldsymbol{x}}_t - \boldsymbol{x}_t\right\|^2_{\boldsymbol{Q}_t}} + \boxed{\left\|\boldsymbol{u}_t\right\|^2_{\boldsymbol{R}_t}}$$

$$\text{s.t.} \quad \boxed{\dot{\boldsymbol{x}}_t = \boldsymbol{A}\boldsymbol{x}_t + \boldsymbol{B}\boldsymbol{u}_t}$$

System dynamics



Model predictive control (MPC):

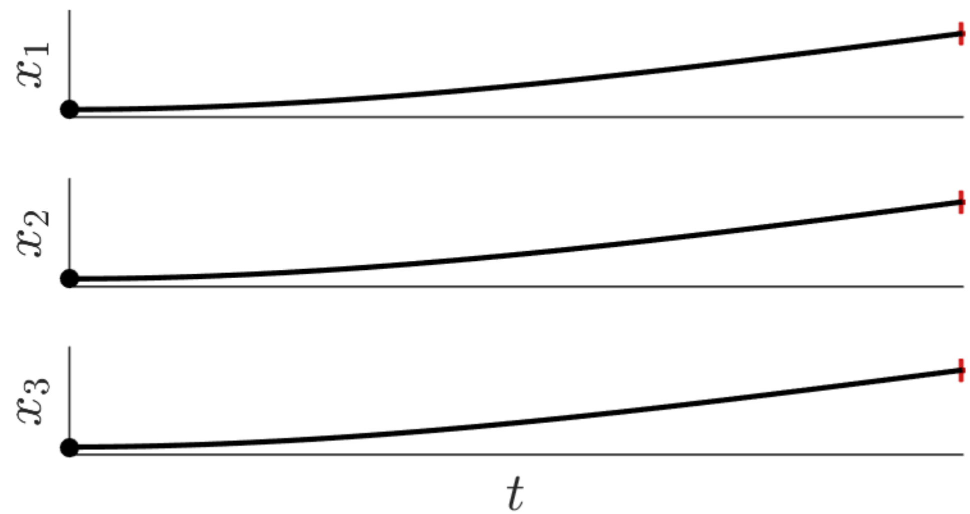
$\boldsymbol{x}_t$ state variable (position+velocity)

$\hat{\boldsymbol{x}}_t$ desired state

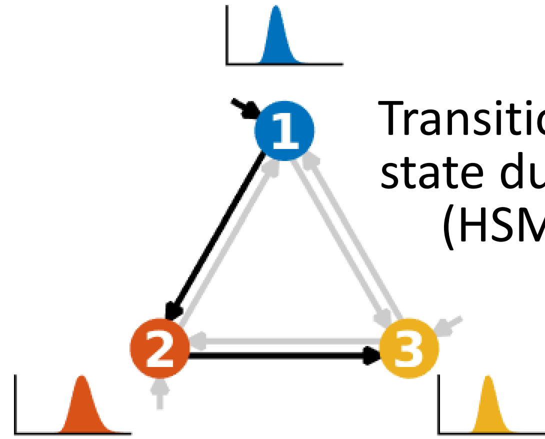
$\boldsymbol{u}_t$ control command (acceleration)

$\boldsymbol{Q}_t$ precision matrix

$\boldsymbol{R}_t$ control weight matrix



Learning minimal intervention controllers



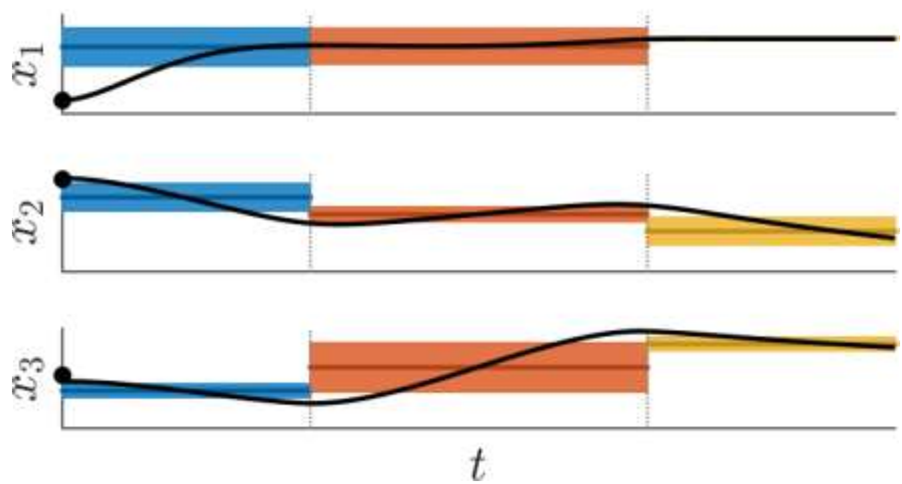
Transition and state duration (HSMM)

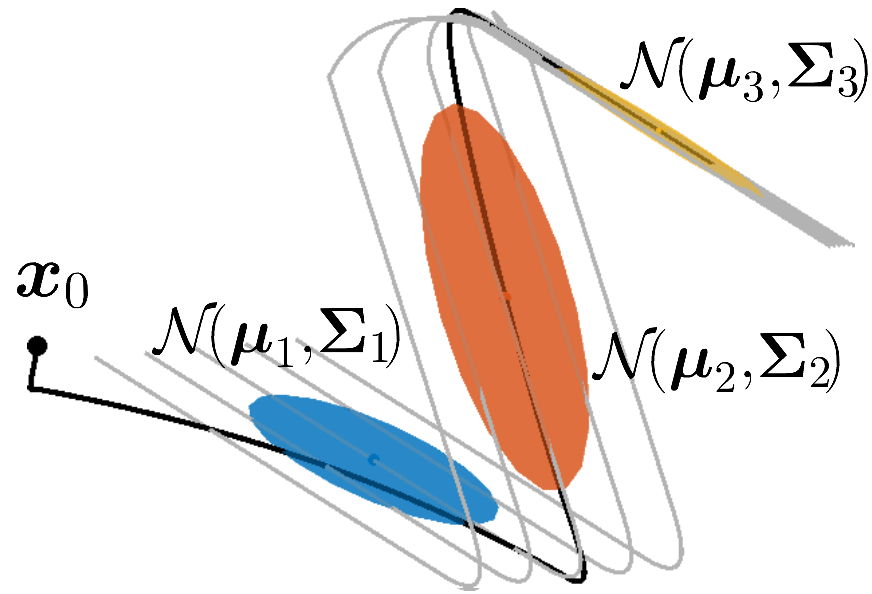
➡ **Analytical solution to generate movements by following minimal intervention control principle**

Stepwise reference path given by:

$$\hat{\boldsymbol{x}}_t = \boldsymbol{\mu}_{s_t} \quad \boldsymbol{Q}_t = \boldsymbol{\Sigma}_{s_t}^{-1}$$

s_t **111111111222222222222333333333**

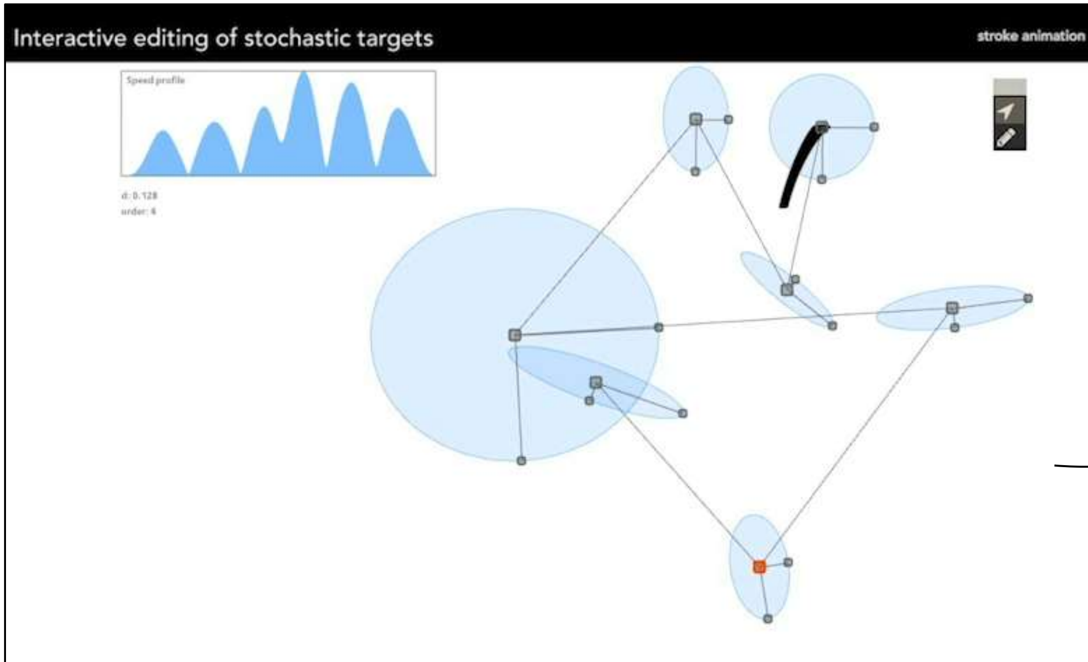




$\boldsymbol{\mu}_i$ center of the Gaussian

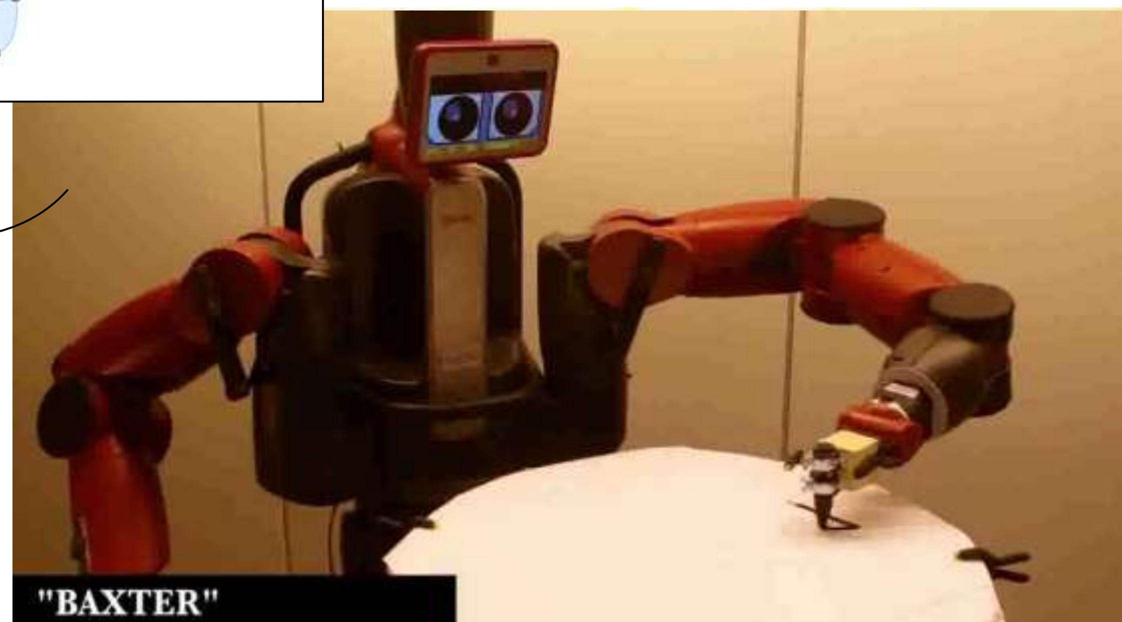
$\boldsymbol{\Sigma}_i$ covariance matrix

Application: Editing movements with variations



User interface to edit and generate natural and dynamic motions by considering variation and coordination

Compliant controller to retrieve safe and human-like motions



Daniel Berio

Frederic Fol Leymarie

idiap RESEARCH INSTITUTE

Goldsmiths UNIVERSITY OF LONDON

[Berio, Calinon and Leymarie, IROS'2016] [Berio, Calinon and Leymarie , MOCO'2017]

Application: Assistive dressing

SNSF, CHIST-ERA (2015-2018)
https://i-dress-project.eu

Emmanuel Pignat

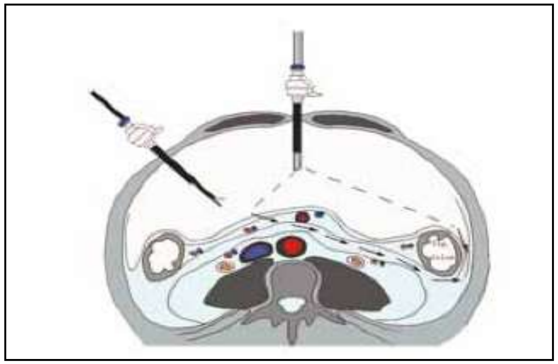
[Pignat and Calinon, RAS 93, 2017] [Canal, Pignat, Alenya, Calinon and Torras, ICRA'2018]

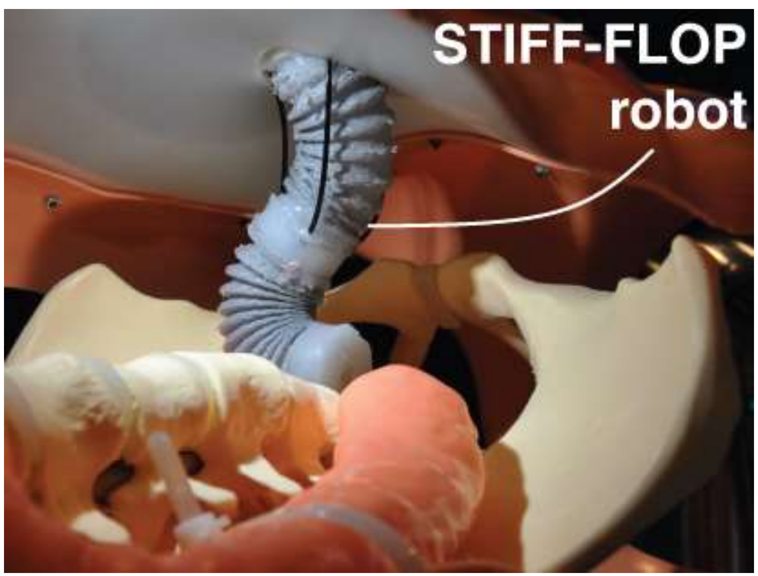
Application: Minimally invasive surgery

STIFF flop

FP7 (2012-2015)

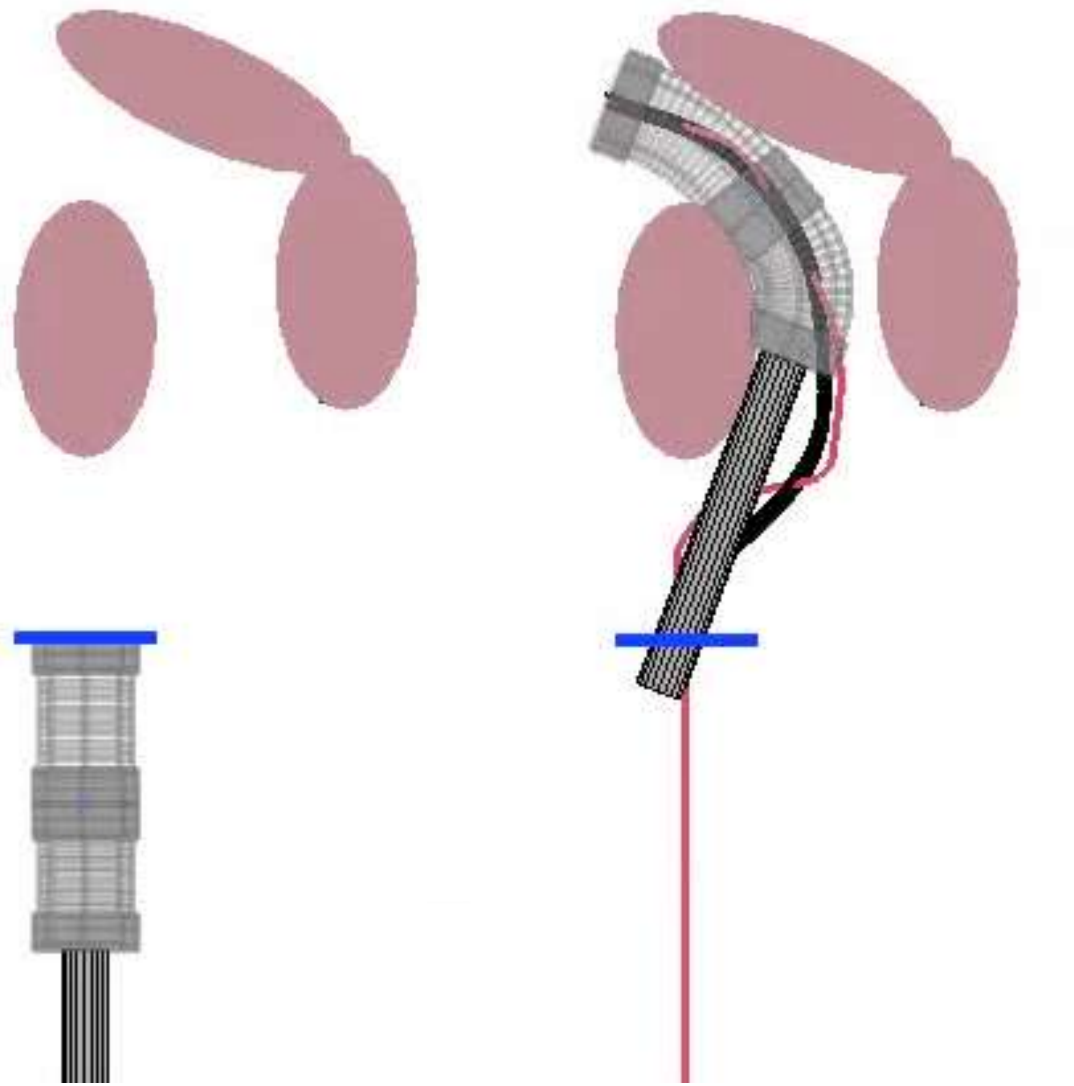
iit ISTITUTO ITALIANO DI TECNOLOGIA





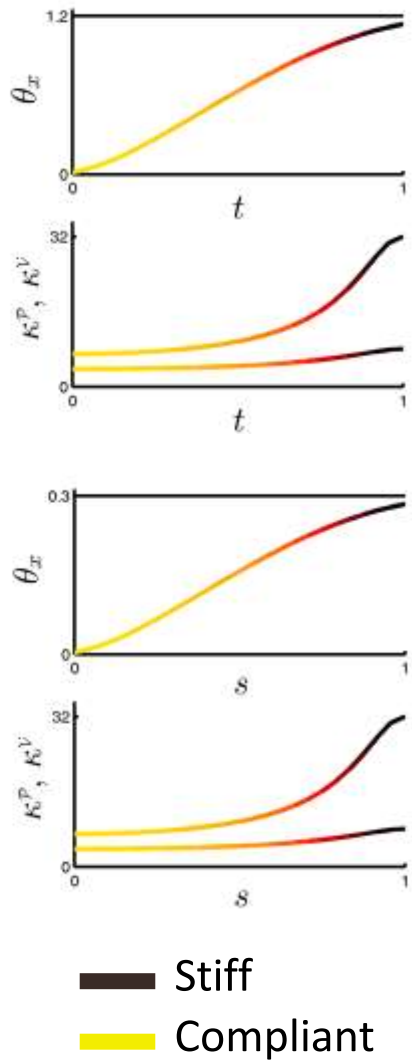
Insertion

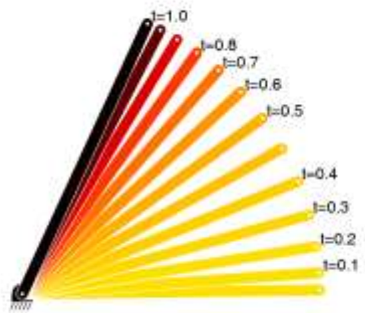
Retraction

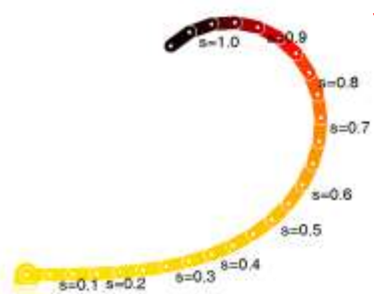


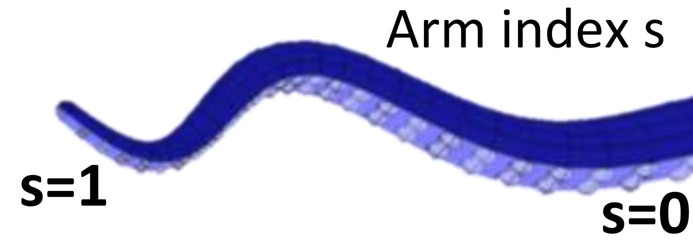
[Bruno, Calinon and Caldwell, Autonomous Robots, 2016]

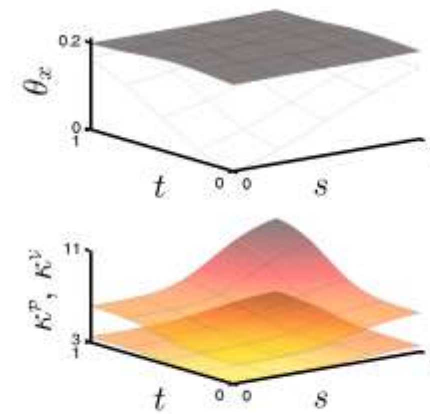
Application: Minimally invasive surgery

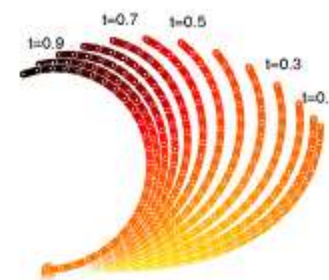


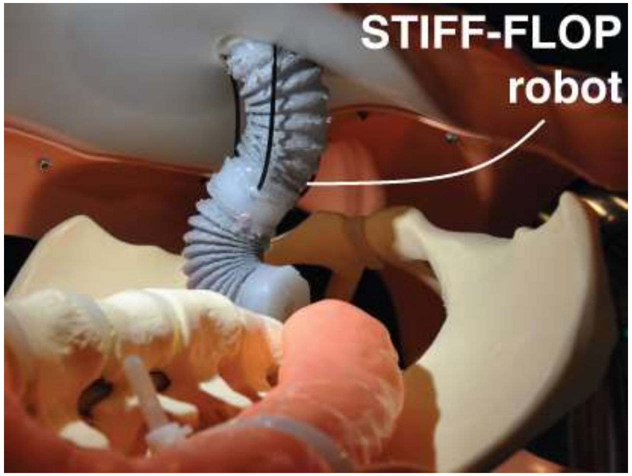












[Bruno, Calinon, Malekzadeh and Caldwell, ICIRA, LNCS 9246, 2015]

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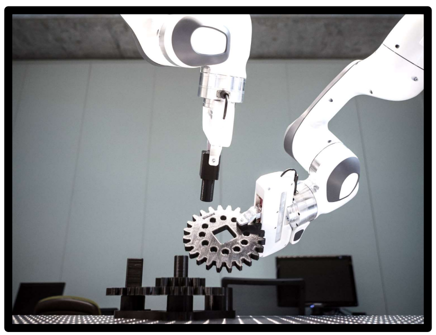
Prior 1: Natural movements are driven by minimal intervention control principles



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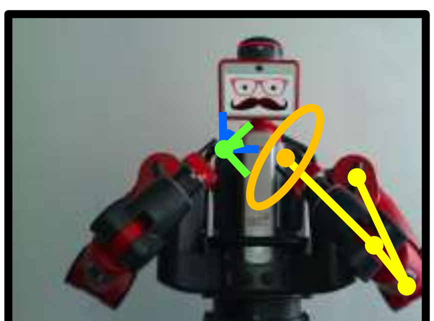
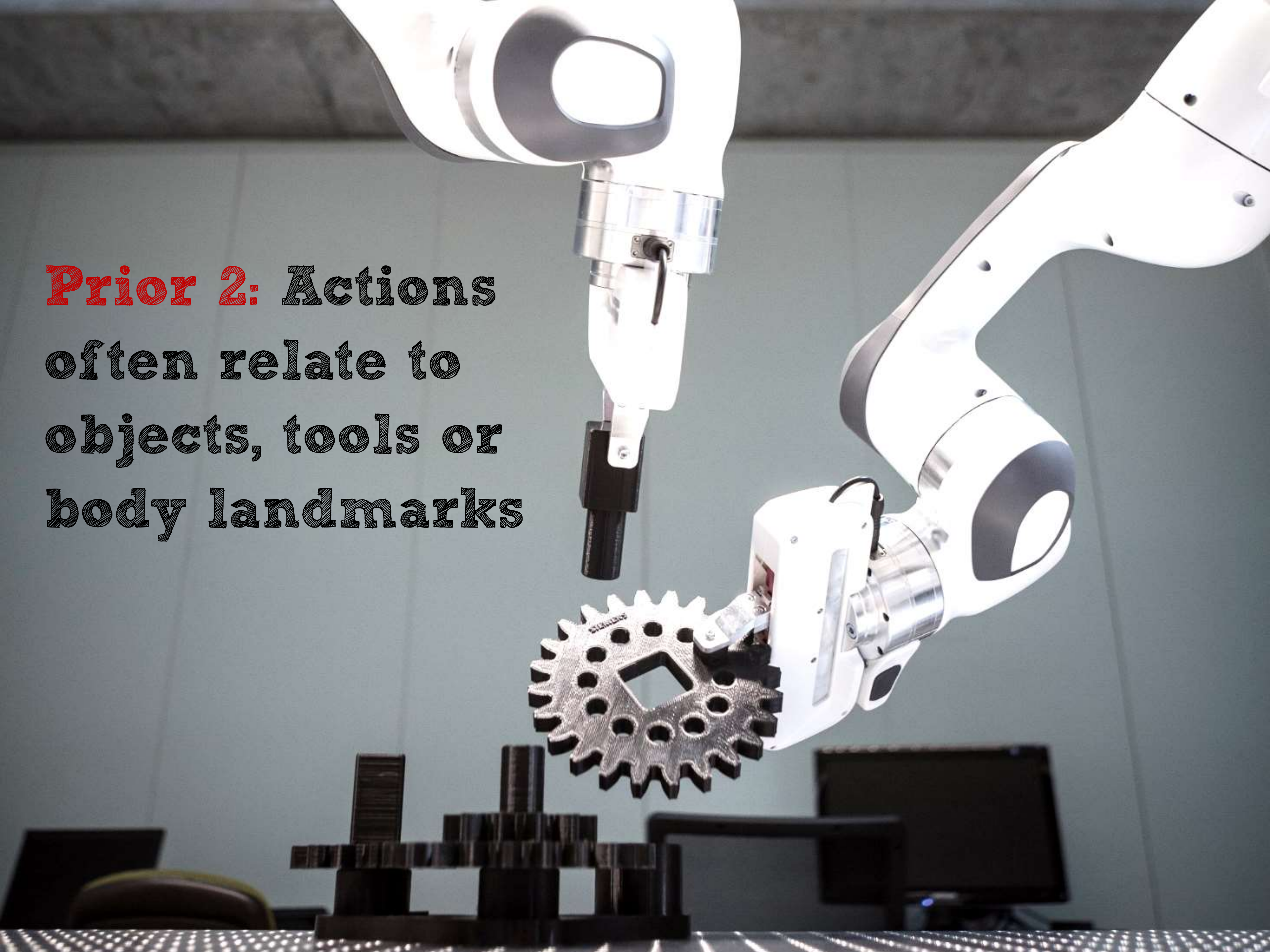


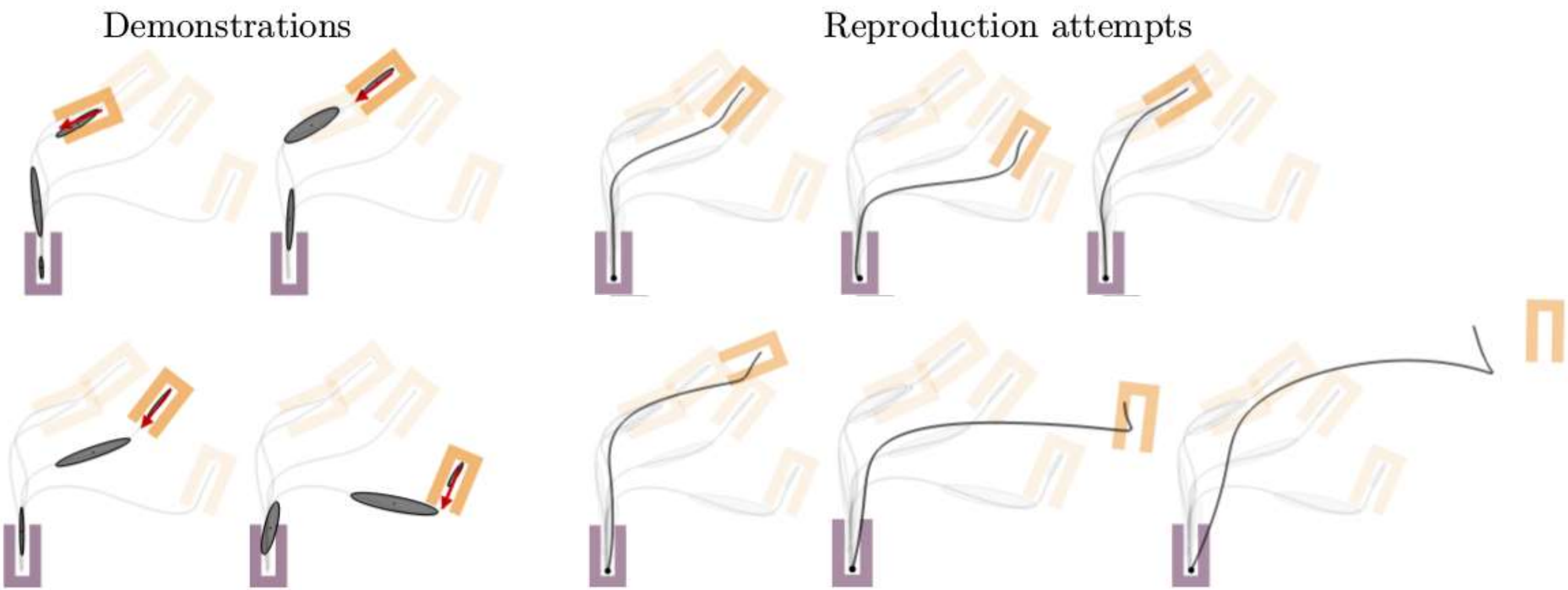
Prior 3: Diverse data in robotics lie on structured manifolds


Prior 2: Actions
often relate to
objects, tools or
body landmarks

Conditioning-based approach

Regression with a context variable *c*:

- Learning of $\mathcal{P}(\boldsymbol{c}, \boldsymbol{x})$
- Retrieval with $\mathcal{P}(\boldsymbol{x}|\boldsymbol{c})$



→ Generic approach, but limited generalization capability

Control in multiple coordinate systems

Track path in coordinate system j

$$\min_{\boldsymbol{u}} \sum_{t=1}^{T} \sum_{j=1}^{P} \left\| \hat{\boldsymbol{x}}_t^{(j)} - \boldsymbol{x}_t \right\|^2_{\boldsymbol{Q}_t^{(j)}} + \left\| \boldsymbol{u}_t \right\|^2_{\boldsymbol{R}_t}$$

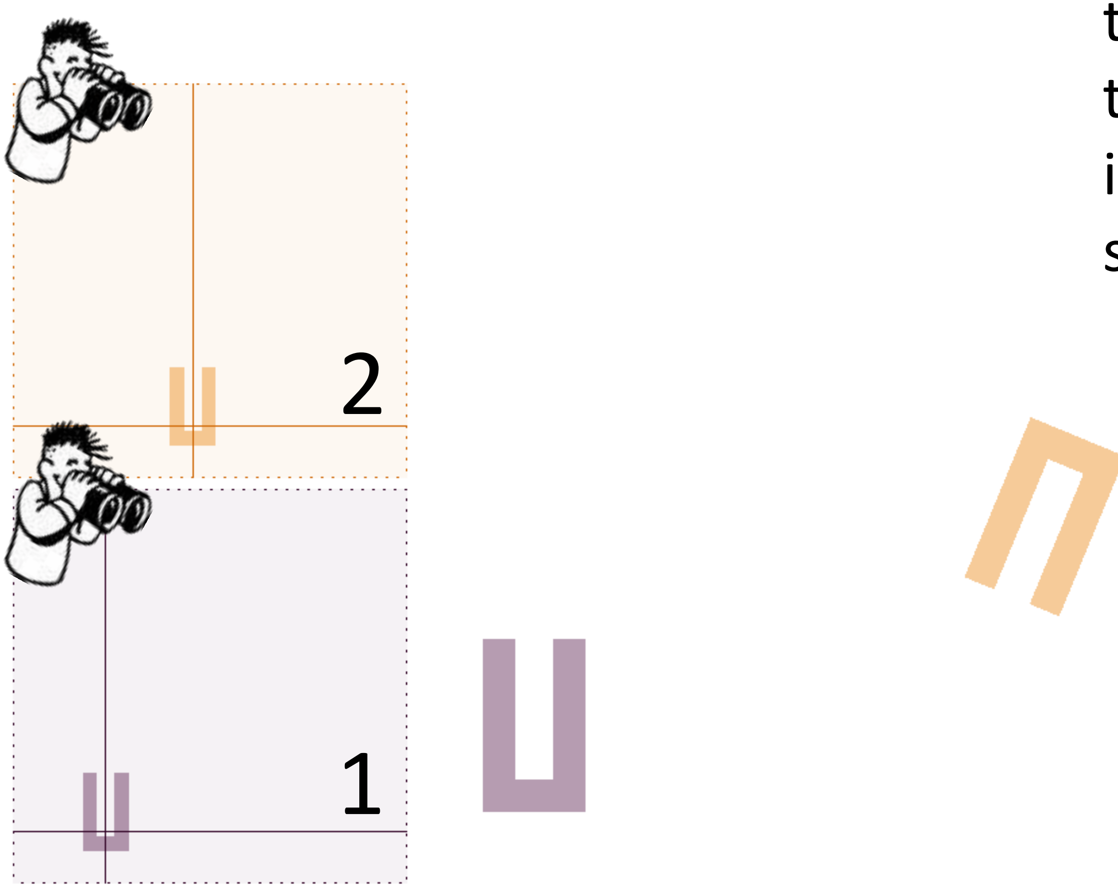
Use low control commands!

$$\text{s.t.} \quad \dot{\boldsymbol{x}}_t = \boldsymbol{A}\boldsymbol{x}_t + \boldsymbol{B}\boldsymbol{u}_t$$

Control in multiple coordinate systems

$$\min_{\boldsymbol{u}} \sum_{t=1}^{T} \sum_{j=1}^{P} \left\| \boldsymbol{\mu}_t^{(j)} - \boldsymbol{x}_t \right\|^2_{\boldsymbol{Q}_t^{(j)}} + \left\| \boldsymbol{u}_t \right\|^2_{\boldsymbol{R}_t}$$

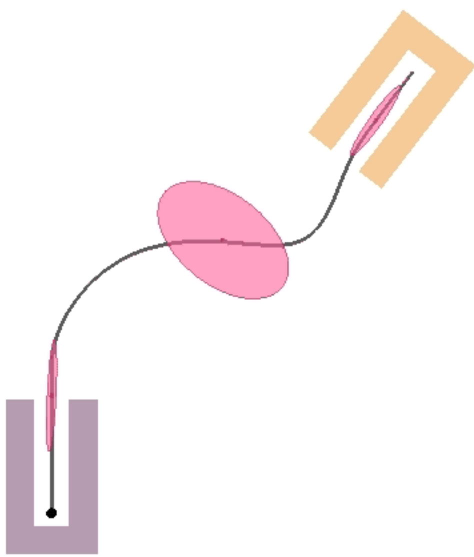
In many robotics problems, the parameters describing the task or situation can be interpreted as coordinate systems



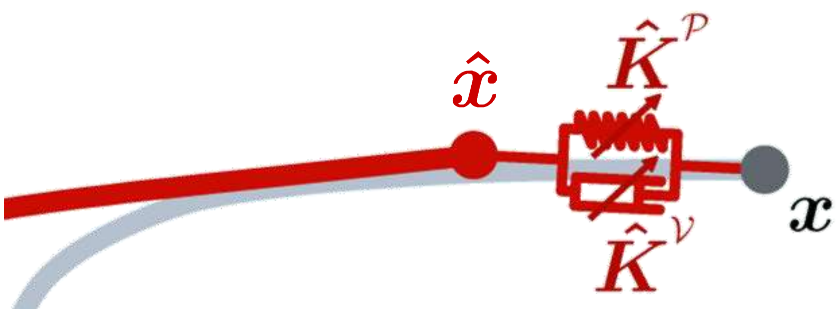
[Calinon, HFR’2016]

Control in multiple coordinate systems

$$\min_{\boldsymbol{u}} \sum_{t=1}^{T} \sum_{j=1}^{P} \left\| \boldsymbol{\mu}_t^{(j)} - \boldsymbol{x}_t \right\|^2_{\boldsymbol{Q}_t^{(j)}} + \left\| \boldsymbol{u}_t \right\|^2_{\boldsymbol{R}_t}$$



➡ **Learning of a controller**
(instead of learning a trajectory) that adapts to new situations while **regulating the gains** according to the precision and coordination required by the task



[Calinon, HFR'2016]

Control in multiple coordinate systems

$$\min_{\boldsymbol{u}} \sum_{t=1}^{T} \sum_{j=1}^{P} \left\|\boldsymbol{\mu}_t^{(j)} - \boldsymbol{x}_t\right\|^2_{\boldsymbol{Q}_t^{(j)}} + \left\|\boldsymbol{u}_t\right\|^2_{\boldsymbol{R}_t}$$

➡ Retrieval of control commands in the form of trajectory distributions, facilitating exploration and adaptation (in either control or state space)

[Calinon, HFR'2016]

Application: Shared control

DexROV

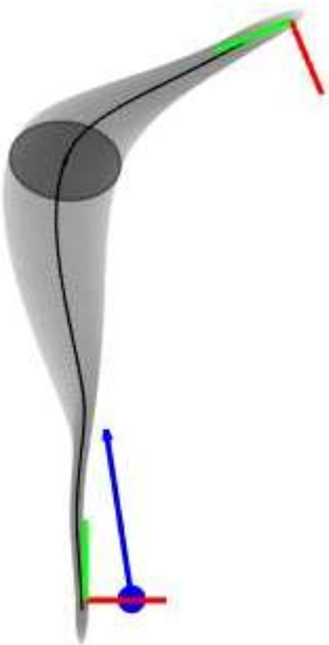
Dr Andras Kupcsik

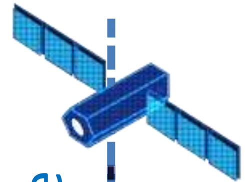
http://dexrov.eu

EC, H2020 (2015-2018)

Application: Shared control

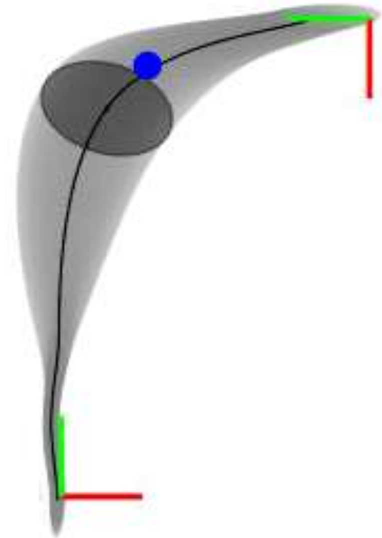
DexROV http://dexrov.eu
EC, H2020 (2015-2018)





Teleoperator side

Robot side



only Gaussian ID
is transmitted

[Birk *et al.*, IEEE Robotics and Autom. Magazine, 2018 (in press)] [Havoutis & Calinon, Autonomous Robots, 2018]

Application: Coordination and co-manipulation

[Silvério et al., IROS’2015]

[Rozo et al., IROS’2015]

[Rozo et al., IEEE T-RO 32(3), 2016]

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TECNOLOGIA

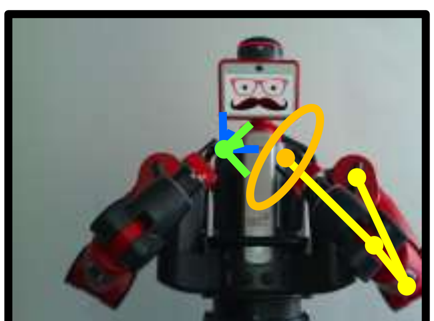
Dr Leonel Rozo

Dr João Silvério

Outline

Prior 1: Natural movements are driven by minimal intervention control principles

Prior 2: Actions often relate to objects, tools or body landmarks



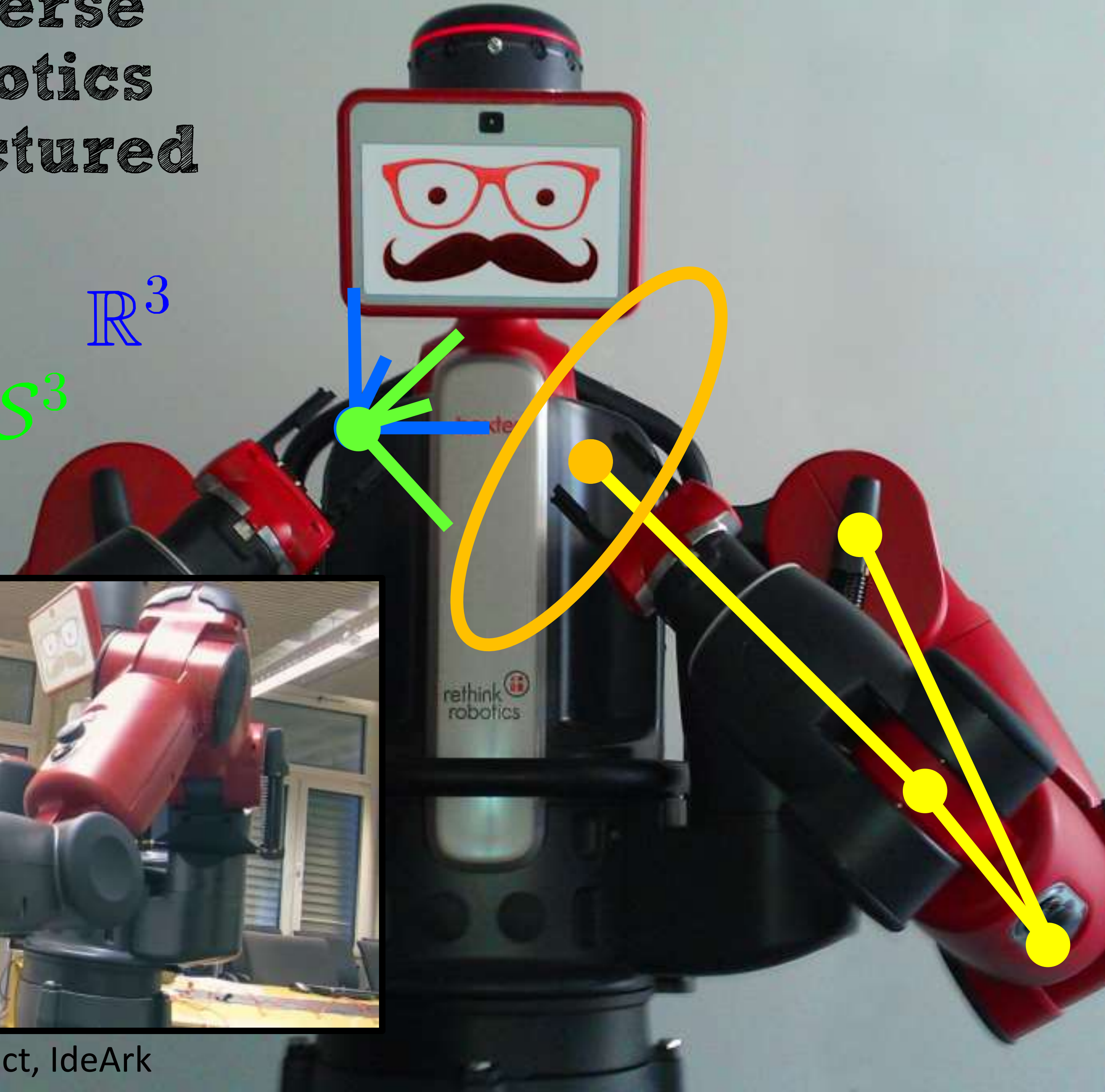
Prior 3: Diverse data in robotics lie on structured manifolds

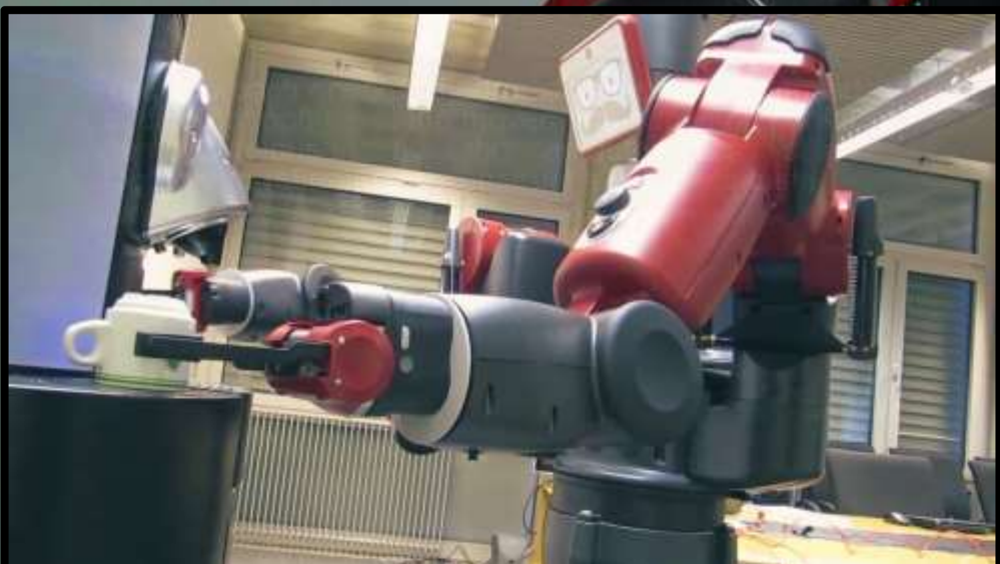
Prior 3: **Diverse data in robotics lie on structured manifolds**

$\mathcal{S}^1 \times \mathcal{S}^1 \times \ldots$ $\quad \mathbb{R}^3$

$\mathrm{SE}(3)$, $\mathbb{R}^3 \times \mathcal{S}^3$

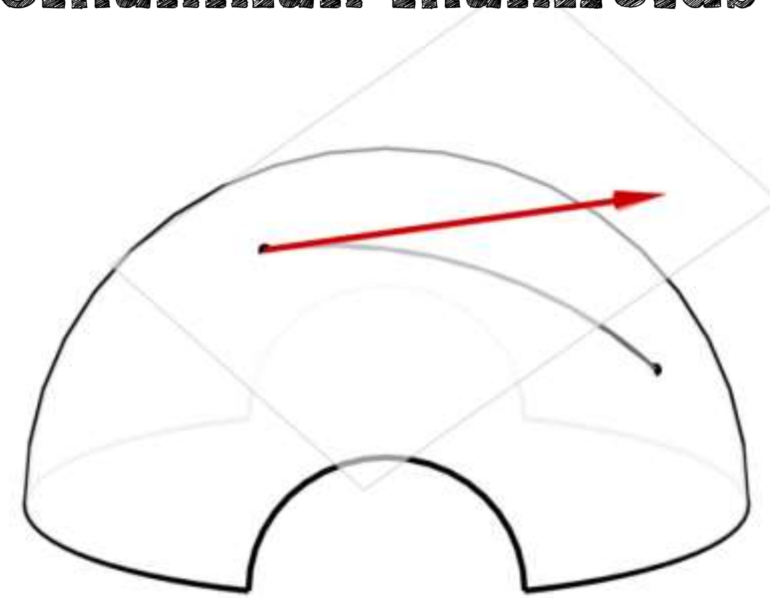
$\mathcal{S}^6_{++}$



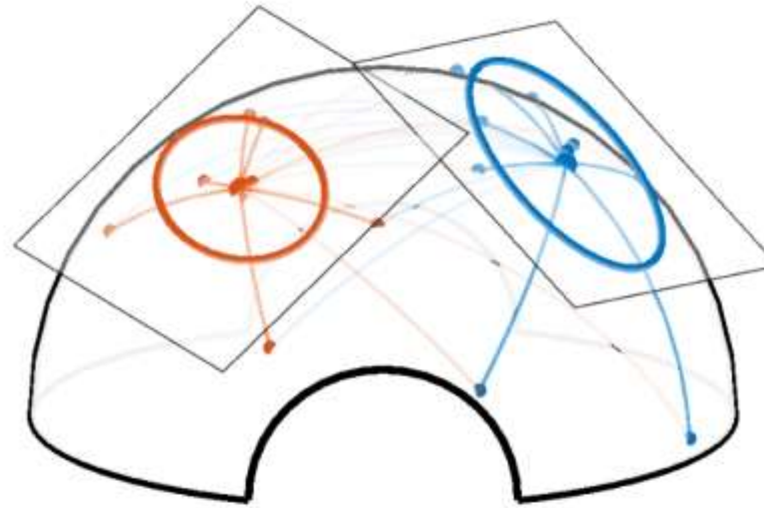


“Baxter: What Else?” project, IdeArk

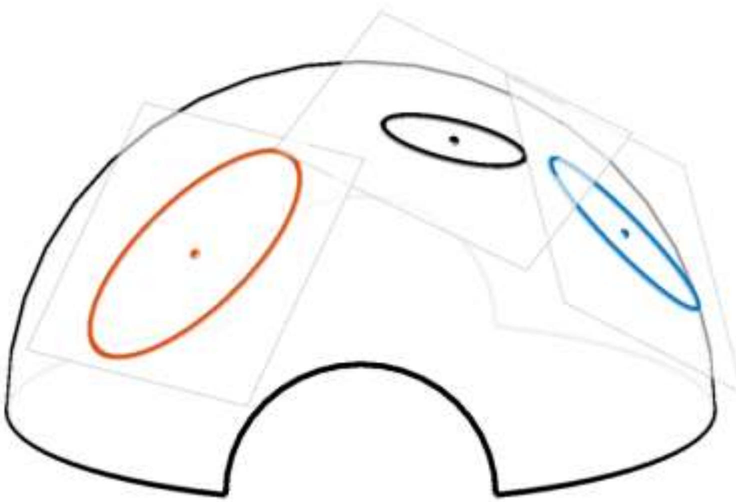
Riemannian manifolds



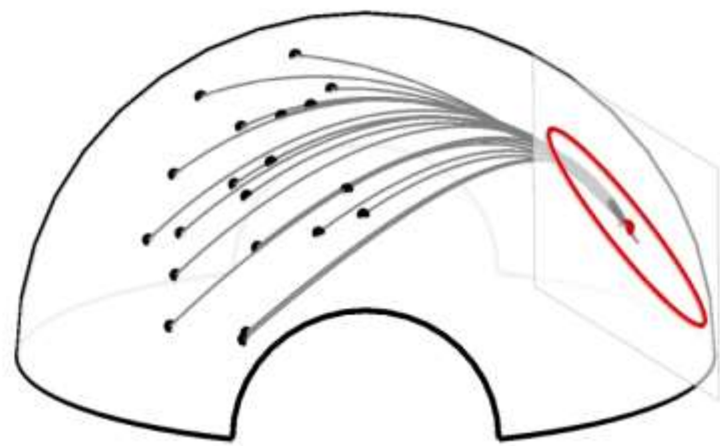
Interpolation and extrapolation



Clustering and distribution



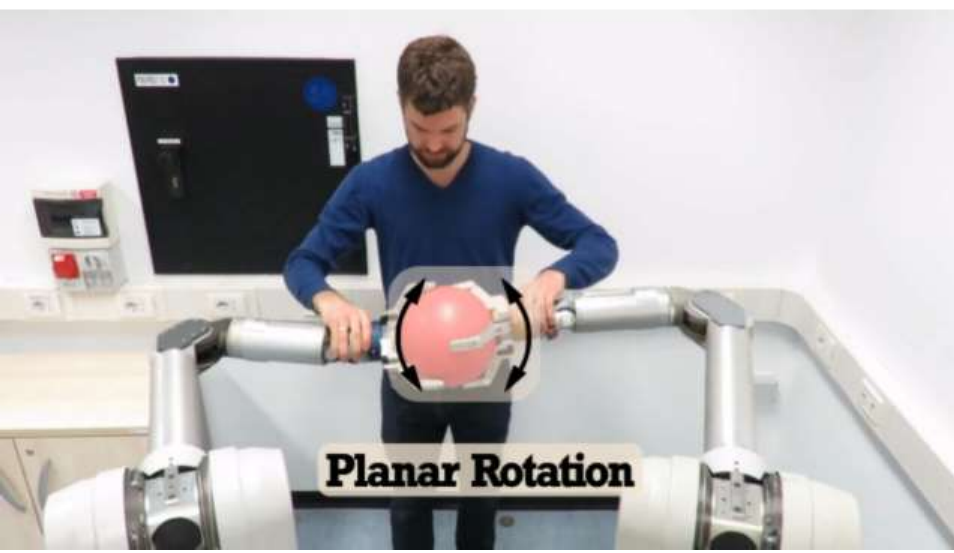
Fusion of sensing/control information

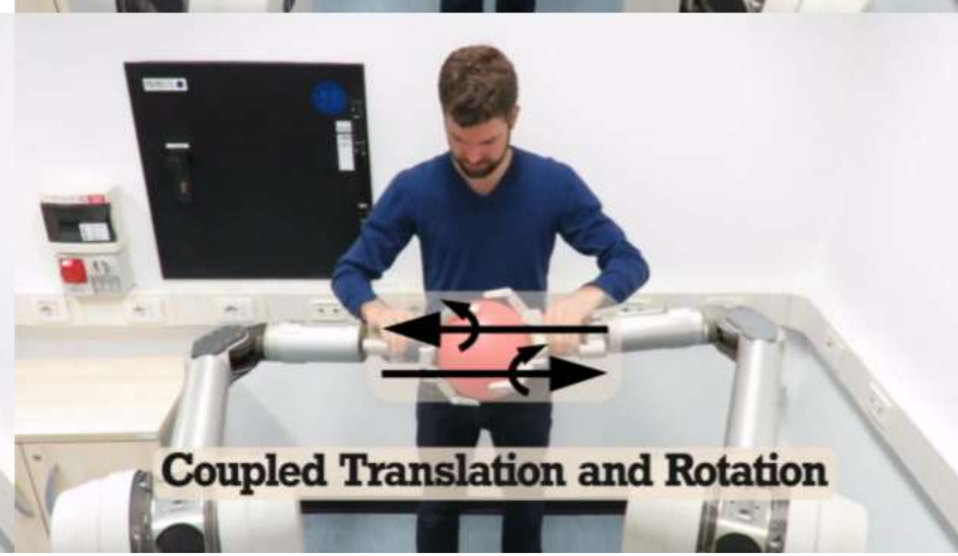


Linear quadratic tracking

Impedance control on Riemannian manifolds

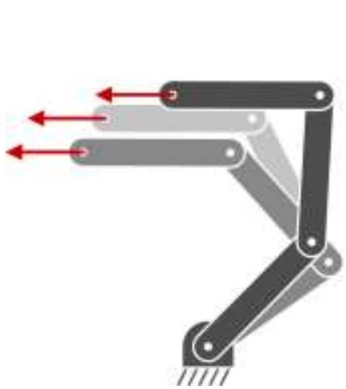
We demonstrate three different tasks, each requiring a different synergy between the end-effectors.

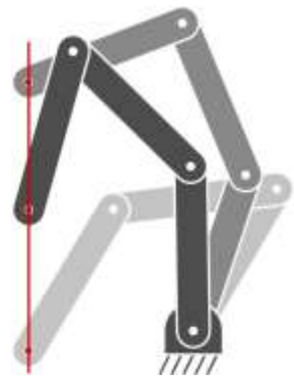


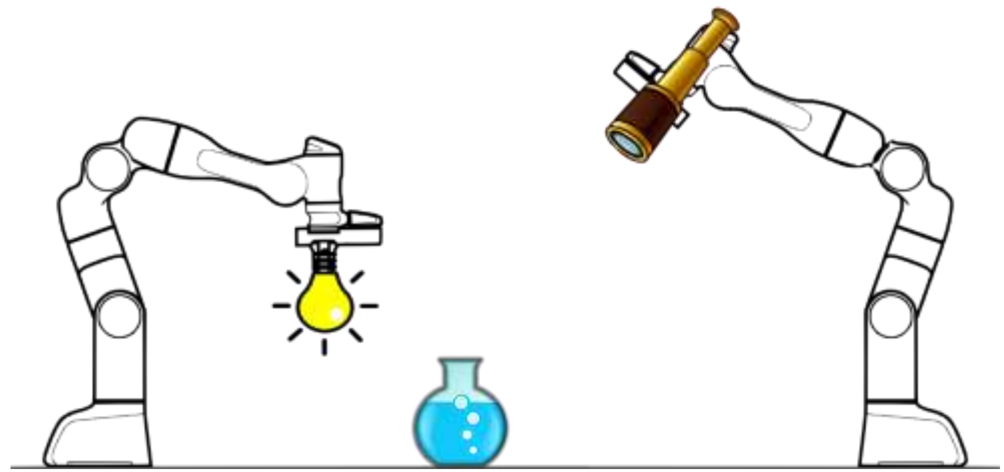


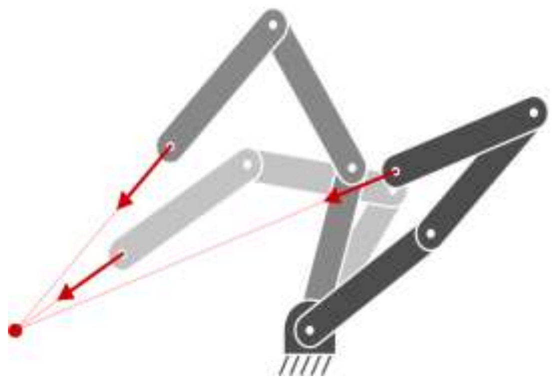
[Zeestraten, Havoutis, Calinon and Caldwell, IROS'17]

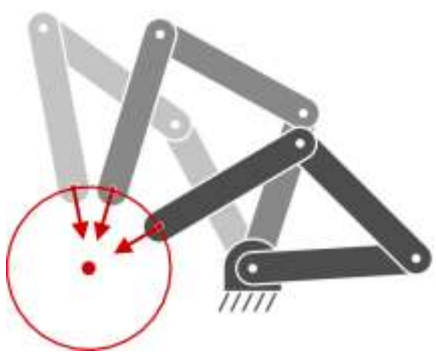
Application within Platform-MMD project

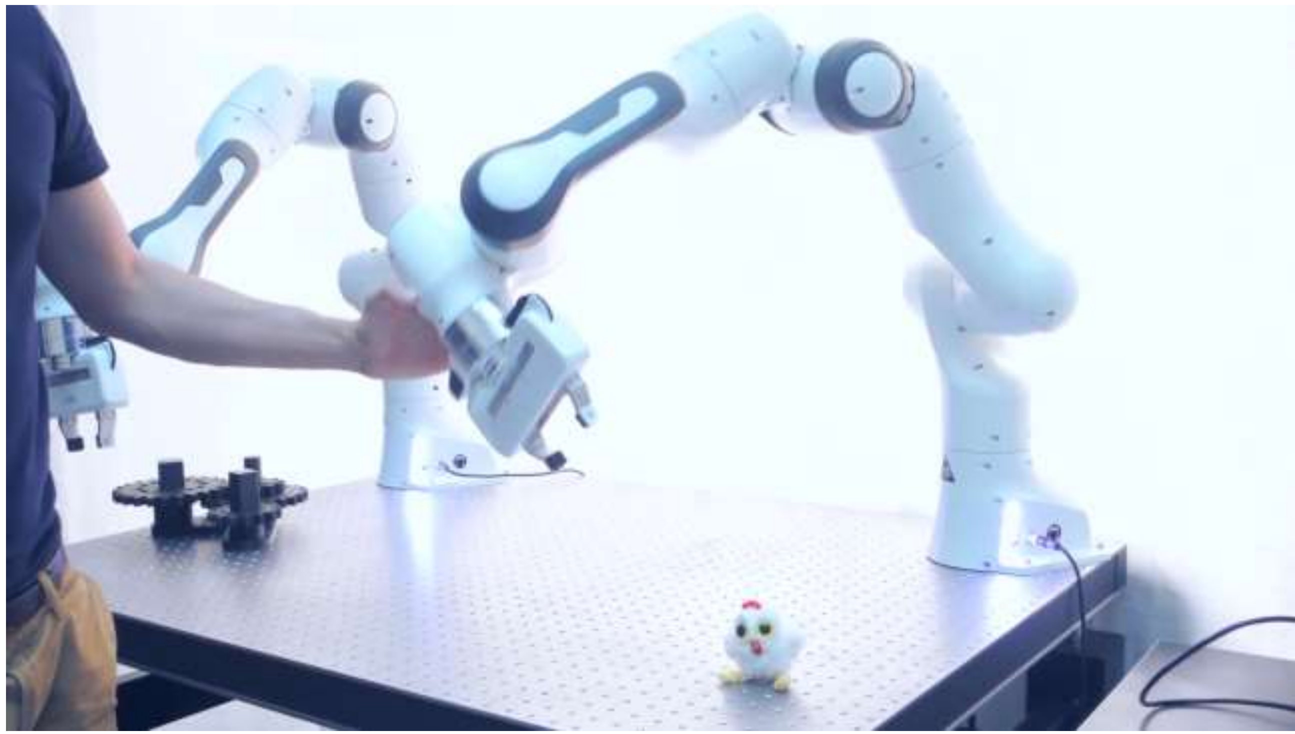






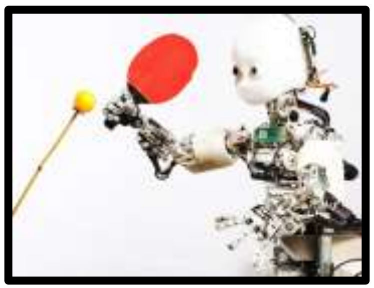




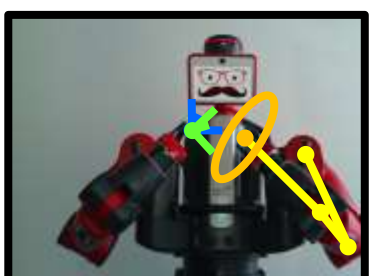


Conclusion

Combining **statistical learning** techniques and **model predictive control** provides a generative approach to the **transfer of skills involving variable impedance**



Statistical learning in **multiple coordinate systems** can be exploited to learn robot skills and behaviors from few demonstrations, with **adaptation to new situations**



Robotics is rich in **structures** and **geometries** that can be exploited to acquire skills and behaviors from a **small set of interactions** (with user or environment)

Source codes (Matlab/Octave, C++ and Python):

http://www.idiap.ch/software/pbdlib/

Contact:

sylvain.calinon@idiap.ch
http://calinon.ch

Robot Learning & Interaction Group at Idiap:


Noémie Jaquier


Emmanuel Pignat


Teguh Lembono


Dr Andras Kupcsik


Thibaut Kulak


Nicolas Desprès


Hakan Girgin


Dr Antonio Paolillo

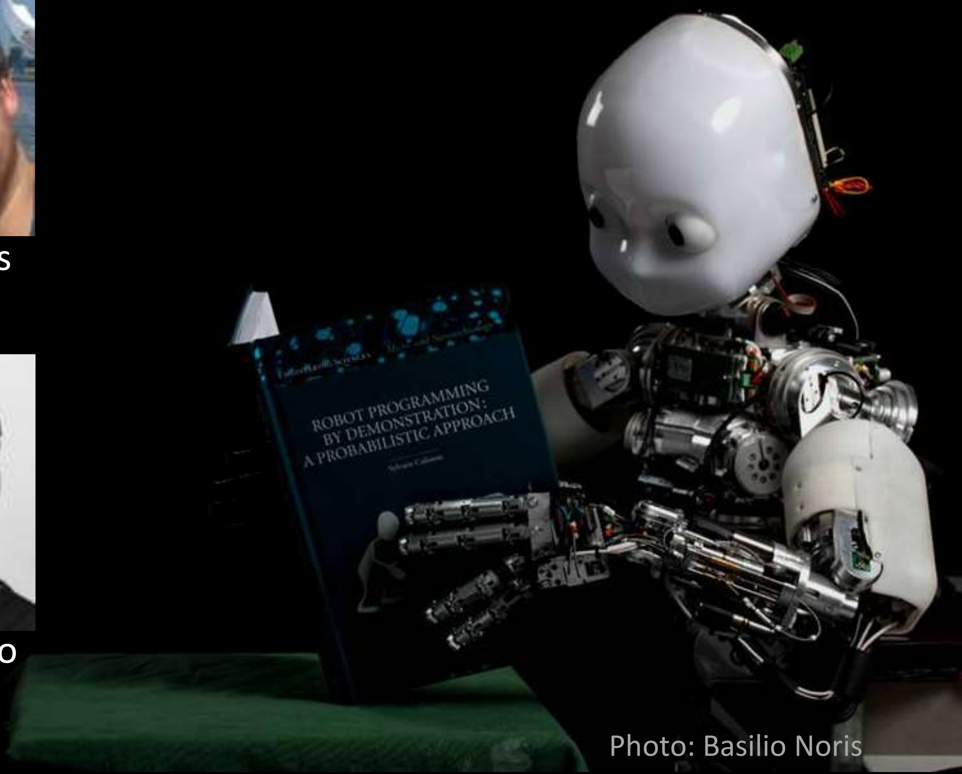


Photo: Basilio Noris